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Monitoring and assessing "ghost cities" in Northeast China from the view of nighttime light remote sensing data

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ABSTRACT

Urbanization has proceeded at an unprecedented speed in China during the last 20 years, resulting in extensive natural landscapes being transformed into impervious surface. The "ghost city" phenomenon has emerged due to the unreasonable urban expansion which far exceeds the actual demand of human habitat. Previously, few research studies have provided objective and sufficient knowledge with regard to identify "ghost cities" and their spatial distribution. In this paper, we proposed an effective and feasible framework to monitor and evaluate "ghost cities" utilizing nighttime light imagery obtained from day-night band (DNB) of Visible Infrared Imaging Radiometer Suite (VIIRS). We established a "ghost city" index (GCI) to quantify the intensity of the phenomenon in the northeast of China, and analyzed the spatial pattern of "ghost cities" for different GCI classes. Our results indicate that the intensity of "ghost city" phenomenon decrease from regions adjacent to the border to interior areas, whilst regions with extremely high GCI are mostly districts and county cities. Tests of typical regions show that non-lit built-up area for high GCI regions is spatially clustered and low population regions have a high tendency to suffer from the "ghost city" phenomenon. Therefore, our findings provide a spatial-explicit insight into the "ghost city" phenomenon, and consequently can be beneficial to assist sustainable urban planning.

1. Introduction

Since the implementation of the reform and open policy in the late 1970s, China has experienced rapid urbanization (Li, Wu, Huang, Sloan, & Skitmore, 2017). Simultaneously, the urban area, as the major habitat for human beings, has expanded unprecedentedly in both velocity and intensity, which was reported six times larger in 2011 compared with 1978 (Kuang, Chi, Lu, & Dou, 2014).

In growing economics, the need to develop urban areas can often lead to poor planning and in-efficient urban design (Campbell, 1996; Zhou, Xu, Wang, & Lin, 2015). The uncontrolled urban expansion has given rise to the "ghost city" phenomenon, which has attracted great attention of the society in recent years (Zhou, Ma, Zhou, & Xu, 2015). Shepard (2015) gave the definition of "ghost cities" in his book, named "Ghost City of China", as "a new development that is running at severe undercapacity, a place with drastically fewer people and business than there is available space for". Specifically, the population density of the "ghost city" is low, and the irrational construction leads to a high housing vacancy rate with weak luminosity in the built-up area at nocturnal time (Chen et al., 2015). Meanwhile, these regions have wasted massive resources and land, drawing a negative impact on regional economic coordination and development (Nie & Liu, 2013). Therefore, it is of crucial importance to probe into "ghost city" phenomenon, subsequently seeking effective solution to monitor and mitigate the phenomenon.

Few research studies have investigated into "ghost city" phenomenon in China (Yao & Li, 2011). The majority of interesting regarding "ghost cities" in China has been highlighted through public media. However, most of the reports were less credible due to unreliable methods, for example some focused only on hot spots, whilst others were based on taking pictures of counting the number of homes with lights on at night (Chi, Liu, & Wu, 2015). Since 2014, an annual ranking list of "ghost city" has been published by Standard Ranking, a Chinese third-party organization, which used the ratio of built-up area and the population as an indicator of "ghost cities" (Standard Ranking, 2015). Yet, the list only covered prefecture cities and part of county cities in

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China, and the statistical data often suffered from time-lagging problem. Chi et al. (2015) used positioning data derived from Baidu Map (a mobile map app), to represent the spatial distribution of the vacant housing areas in China. However, the positioning data was obtained from only one of the mobile map apps, and people who did not use the app or even those without phones were not considered as well. More importantly, most of the studies failed to capture the spatial distribution of "ghost cities". Thus, there is an urgent need to develop a feasible and spatial-explicit method to provide insight into the "ghost city" phenomenon.

Remote sensing which has been widely applied in urbanization studies, presents multiple advantages in comprehending this phenomenon, such as spatial consistency and wide coverage area (Deng, Wang, Hong, & Qi, 2009; Xie & Weng, 2016). Nonetheless, traditional remote sensing data typically reflects land surface coverage information, and is incapable to exhibit human activity and consequently this "ghost city" phenomenon directly. Nighttime light imagery, as a new type of remote sensing data, is able to detect anthropogenic luminosity at night and therefore has been used as an effective proxy for human activities (Yue, Zhang, & Liu, 2016; Zhang & Su, 2016). It has been extensively applied in socioeconomic statistics estimation (Gao, Huang, He, Sun, & Zhang, 2016; Yu et al., 2015), and urbanization monitoring (Cai, Huang, & Song, 2017; Zhang & Seto, 2011). Suomi National Polar-orbiting Partnership (Suomi-NPP) satellite was launched in 2011, and its day-night band (DNB) of the Visible Infrared Imaging Radiometer Suite (VIIRS) shows superiority over the former sensor Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS). Specifically, DNB does not only have an onboard calibration system, but also a higher spatial resolution (742 m) as well as a wider detection range (down to 2×10^{-11} w/cm^2/sr) (Levin & Zhang, 2017; Zhang, Wu, Peng, & Cao, 2017). Subsequently, there is an increasing trend to take advantage of DNB in recent studies (Chen et al., 2017; Elvidge, Zhizhin, Hsu, & Baugh, 2013; Li, Xu, Chen, & Li, 2013).

To the best of our knowledge, few studies have applied remote sensing data to analyze the "ghost city" phenomenon in China. The overall objective of this study is to propose a feasible and night-time light remote sensing data based framework to evaluate the "ghost city" phenomenon intensity in the northeast of China and to probe into the spatial characteristic of "ghost cities".

2. Study area and datasets

2.1. Study area

Four provinces, located in the northeast of China, were selected as our study area, including Heilongjiang, Jilin, Liaoning and Inner Mongolia (Fig. 1). The study area covers 1.99 million km^2 (22.25% of the mainland area) with a population of 134.82 million. With numerous large-scale industrial bases, urbanization has taken place at a considerable speed. Nonetheless, these provinces have shown a noticeable trend of economic downturn in the past 10 years, and many cities have been reported to suffer from the "ghost city" phenomenon.

2.2. Datasets

This study used two land cover type product datasets, including MODIS Land Cover Type Yearly Composite Product (MCD12Q1, IGBP classification scheme, 2013) and GlobeLand 30 dataset (GL30, 2010). MCD12Q1 product was downloaded from USGS Land Processes Distributed Active Archive Center (LPDAAC) (https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd12q1, last access: March 15, 2016). GL30 dataset is a 30 m-resolution global land cover classification product released by National Standard geography information Center and was downloaded from Globe Land Cover Information Service (http://www.globallandcover.com/GLC30Download/index.aspx, last access: April 9, 2016). The land cover types were extracted from Landsat5, Landsat7 and HJ-1 during 2009–2011 with an 83.51% classification accuracy. Additionally, the MCD12Q1 dataset, with a coarse resolution (500 m) and 74.8% classification accuracy, was incapable of representing the real range of built-up area (Fig. 4a). Furthermore, there was no land cover type datasets available with a 30 m resolution for the year of 2013. Hence, we combined MCD12Q1 with GL30 to improve the accuracy, and the methodology is demonstrated in section 3.1.

We utilized the version 1 VIIRS DNB data (15 arc-second) retrieved in January 2014, downloaded from the NOAA National Centers for Environmental Information (NCEI) (https://www.ngdc.noaa.gov/eog/viirs/download_monthly.html, last access: March 15, 2016).

Two additional datasets were included: (1) Landsat 8 OLI (2013), which was downloaded from (http://www.gscloud.cn/, last access: April 29, 2016); (2) Land use change survey data (2013), provided by local Bureau of Land and Resources, is an annually updated land use map, whose land use type was derived by visually interpreting high resolution remote sensed and aerial images.

3. Methods

3.1. Built-up area identification

In order to obtain an accurate built-up area, we proposed a method to fuse MCD12Q1 and GL30, which was based on the assumption that the built-up area would not decrease from 2010 to 2013, as previous studies have shown that this is an appropriate method when applied to countries under rapid urbanization (Shi et al., 2016; Xie & Weng, 2016). First, all images were re-projected into Albers conical equal-area projection and resampled to 500 m resolution. Then, we created a built-up/non-built-up binary map for MCD12Q1 and GL30 (Fig. 4a). According to the assumption, we took the union of two datasets, which meant that the built-up pixels in either dataset would be added to the output map (Fig. 4b).

As Fig. 4b shows, the union data contains massive isolated and scattered pixels, most of which are rural settlements distributed in the peri-urban and mountainous area. It is "ghost city" phenomenon in continuous built-up areas rather than distant rural areas that this study focuses on. To remove these pixels, a two-step majority filter was applied, which could replace the center pixel based on the majority of their contiguous neighboring pixels. The filter was implemented in ArcGIS environment (for more information, please refer to ArcGIS Help, http://resources.arcgis.com/en/help/). It has two criteria to satisfy before replacing the value of center pixel by majority value. First, the neighboring pixels must be directly contiguous to the center pixel. Second, the number of neighboring pixels with the same value must be large enough to be the majority value. In other words, for the first filter step, three out of four pixels must have the same value, and for the second step two out of four pixels must have the same value.

3.2. Validation of the identified built-up area

In order to produce the ground truth built-up area to validate the built-up area that we identified by fusing MCD12Q1 and GL30, we extracted the built-up area of several typical regions by manually interpreting Landsat 8 OLI image (Fig. 4d), which was displayed with RGB composite using band 6, 5 and 4. The boundaries of these areas were checked and modified utilizing land use change survey data. Following this procedure, we obtained a high accuracy built-up area as ground truth for validation.

3.3. Nighttime light processing

Although most background noise has been masked out in DNB version 1 product, ephemeral lights, such as gas flare and fishing boat, still remain as well as the over-glow effect. Therefore, to eliminate ephemeral lights, a weighted average function was applied to version 1